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Automated Segmentation and Extraction of Area Terrain Features from Radar Imagery

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An automated method for segmenting and extracting certain area terrain features from Synthetic Aperture Radar (SAR) imagery is presented. First, the input radar image is edge-enhanced by passing it through a Sobel operator in order to obtain the required edges for further processing. The unwanted noise, both from the original image source and from the edge operation, is reduced with a low-pass filter. The next step is a region growing process in which pixels of similar gray values in the filtered image are grouped and merged together. A method of selecting an optimum threshold that is essential for region growing is described. The pixels in the image after the region growing operation are further grouped into exactly four different categories, each with its own gray value. The four categories of pixels are then finally classified as water, fields, forests, or urban areas depending upon their gray values. A texture measurement scheme and a Bayes classifier are also incorporated into this effort for verifying the classification results.

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CONTENTS

ILLUSTRATIONS

PREFACE

This work was done under DA Project, 4A161102B52C, Task B, Work Unit 017, "Automated Feature Extraction from All Source Imagery."

The work was performed during the period April 1987 to March 1989 under the supervision of Dr. Frederick W. Rohde, Team Leader, Center for Automated Image Analysis, and Dr. Richard B. Gomez, Director, Research Institute.

Colonel David F. Maune, EN, was Commander and Director, and Mr. Walter E. Boge was Technical Director of the U.S. Army Engineer Topographic Laboratories during the report preparation.

AUTOMATED SEGMENTATION AND EXTRACTION OF AREA TERRAIN FEATURES FROM RADAR IMAGERY

INTRODUCTION

The problem of automatic extraction of terrain features from radar imagery has been the subject of research for some years. In the past, various pattern classification methods have been applied to samples of both Synthetic Aperture Radar (SAR) and aerial photographic imagery. In many cases, better than 90 percent classification accuracy was obtained when the samples classified were homogeneous, and each sample contained only one category of a particular terrain feature.[1,2,3] For all past experiments, an image sample which had a size of 32 by 32 pixels, was used. This sample window size was found to be optimum for our studies, though the size of the sample window can be varied arbitrarily.

One of the major drawbacks of a statistical pattern classification system is that one cannot classify samples containing more than one category. This problem occurred most often when the sample window was moved across the boundary of different image regions or categories. The Radar Image Classification Aid (RICA) was developed to compensate for this problem.[4] By considering the classified results of its surrounding eight other windows, one can use RICA to classify an unknown border window of image sample. The unknown border window was then classified as a particular terrain category if the majority of the surrounding windows also belonged to that same category. Although RICA produced an improved accuracy for SAR image classification, the boundary edges between different terrain categories were not retained. A totally different approach is taken in this paper to overcome this drawback by first segmenting the entire SAR image into a few categories of terrain features where the boundaries are well preserved. Extraction or classification of terrain features can then be easily performed afterwards. In this paper, a technique for effectively segmenting SAR imagery and a method of selecting an optimum threshold, which is essential for region growing, are described. Region growing is the most important step of the image segmentation process presented. Two methods for identifying and classifying the segmented image into proper terrain feature categories are included. The results of the experimentation are presented together with discussions. Finally, the future applications of the techniques are suggested, and conclusions are presented.

SYSTEM DESCRIPTION

The image segmentation and feature extraction techniques that are described concentrate on four categories of terrain features; water, fields, forests, and built-up areas. The SAR imagery to be used was x-band, HH polarization, and was taken over the Elizabeth City, North Carolina, area

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[1] N. D. Fox and P. F. Chen, Improving Classification Accuracy of Radar Image Using a Multiple-Stage Classifier, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, ETL-0502, September 1988, AD-A200 291.

[2] R. A. Hevenor and P. F. Chen, Pattern Classification Techniques Applied to High Resolution, Synthetic Aperture Radar Imagery, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, ETL-0443, November 1986, AD-A183 537.

[3] P. F. Chen, Preliminary Radar Feature Extraction and Recognition Using Texture Measurement, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, ETL-0315, February 1983, AD-A128 394.

[4] D. T. Franks, J. A. Musselman, and J. W. Sapp, Application of Artificial Intelligence (AI) to Radar Image Understanding, prepared by Software Architecture & Engineering, Inc., Arlington, Virginia, for U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, ETL-0387, February 1985, AD-A152 519.

with a UPD-4 radar system. Approximately 200 SAR images were selected, digitized, and stored for the feature extraction work. Each digitized image consists of 512 by 512 pixels representing a ground area of approximately 1.6 by 1.6 square miles. Most of the images selected contain the four categories of area terrain features as stated above and some linear features, such as bridges, roads, railroads, and boundaries between area regions. The algorithms for the automated segmentation and feature extraction process were first written in the LISP programming language and executed on a Symbolics 3670 LISP machine. The same algorithms were later recoded in the C programming language and implemented on a SUN 3/260 microcomputer system in order to transfer them to a development laboratory.

METHODOLOGY

There are several algorithms required to segment and extract area terrain features automatically from SAR imagery. Figure 1 shows the sequence for applying the automated segmentation and feature extraction algorithms to SAR imagery.

PROCEDURE

SOBEL EDGE OPERATION ⟶ LOW-PASS FILTERING ⟶ REGION GROWING ⟶ SIMPLE PIXEL GROUPING ⟶ MAJORITY MERGE RULES ⟶ REGION CLASSIFICATION ⟶ ALTERNATE CLASSIFICATION USING TEXTURE MEASUREMENT AND BAYES CLASSIFIER

Figure 1. The Sequence of Operations for Obtaining a Segmented and Classified SAR Image.

The entire procedure can be divided into three major processes, which will be discussed in detail as follows:

Automated Segmentation. The process for the automated segmentation of SAR images consists of the following steps:

1. Load the desired digitized SAR image from the disk to the computer. The image will be shown in black and white on the display monitor.

2. Based on its gray tone level, each pixel of the image is assigned a corresponding pseudocolor for easy viewing.

3. A Sobel edge operator is moved sequentially through the entire image for edge enhancement. Appendix A describes the Sobel edge operator.

4. In order to eliminate the noise produced by the edge operation and the noise appearing on the original image, a low-pass filter is passed through the whole image. The low-pass filter is described in appendix B.

5. After the low-pass filtering, a technique called *region growing* is used to merge together pixels that have similar gray values. A commonly used simple region growing technique is explained in appendix C. For our case, the region-gowing technique was modified to

become a two-pass process. First, a threshold value T is set. The selection of a threshold value T requires a lengthy process[5] that will be described in detail in a separate section of this paper.

Once the threshold value T is selected, the first pass of the region growing operation is performed as follows. A control pixel for region n (or category n), called P_{cn}, is selected arbitrarily from the image. Usually, the unlabeled upper left pixel in the image is assigned as the control pixel P_{cn}. The next step is to compare the gray value of each pixel sequentially with that of P_{cn} as given by:

$$|G(i,j) - G_{cn}| < T. \tag{1}$$

Where G(i,j) is the gray value of the pixel P(i,j), and G_{cn} is the gray value of the control pixel P_{cn}. The subscript n signifies that the control pixel is for the category n.

The gray values of all pixels that meet the inequality (1) are summed, and the result is added to the gray value of the control pixel. The resulting sum is then saved in a specially designed memory. For a particular category n, this summed quantity is expressed as SUM_n, and is given as follows:

$$SUM_n = G_{cn} + \sum_{\substack{\text{all pixels met}\\ \text{by inequality (1)}}} G(i,j) \tag{2}$$

Otherwise, the pixel under examination is left unlabeled. At the same time a counter C_n is incremented by "1" when a pixel is added to the SUM_n. This counter starts with a content of "1" so that the final count of the counter will indicate the total number of pixels added to the SUM_n. This is expressed for the category n as follows:

$$C_n = 1 + \text{Number of pixels met by the inequality in (1).} \tag{3}$$

This process of comparison continues sequentially for all unlabeled pixels in the image. When the process is completed up to this point, the SUM_n is divided by C_n to obtain an average pixel value for a particular region category n as

$$A_n = \frac{SUM_n}{C_n} \tag{4}$$

The next step is to repeat the entire process described above, or to compute (1) through (4) for the remainder of the pixels left unlabeled until all pixels on the image are labeled and each pixel belongs to a particular region. This completes the first pass of the region growing process. At this point, a number of average pixel values A_n for potential regions will have been computed.

The second pass of the region growing process is similar to that of the first pass except that the control pixel values G_{cn} are replaced by the corresponding average pixel values A_n. Also, when the value of a pixel is compared to a particular average pixel value, and if the absolute value of the difference of the pixels is less than the threshold value, the pixel under examination will be merged to that particular average pixel, rather than adding it into the quantity SUM_n. In other words, the value of the pixel under examination will be set equal to that particular average pixel value that is used to compare it with. This process is explained in appendix C. The second pass of the region growing process will

[5] M. Nagao and T. Matsuyama, A Structural Analysis of Complex Aerial Photographs, Plenum Press, New York, 1980.

continue until each pixel in the image belongs to a particular region category. The entire region growing process will then be complete.

6. The number of region categories created by applying the region growing process usually exceeds four. A simple pixel grouping routine is used here to further group pixels in the region grown image into exactly four categories. This routine functions as follows: The gray value of each pixel in the region grown image is sequentially examined. If it is larger than or equal to 100, then it is set to 150. If it is less than 100, and larger than or equal to 45, then it is set to 65. If it is less than 45, and larger than or equal to 8, then it is set to 25; otherwise, it is set to 4.

Feature Extraction. After the pixel-grouping process, the entire image is segmented into exactly four categories, with each category assuming a different pixel gray value. Classifying the segmented image regions can be done by assigning each terrain feature name to the category with the corresponding gray value. Usually, the first three categories having gray values of 4, 25, and 65 are classified as water, fields, and forests, respectively; while the last region category having many boundaries or edges with a gray value of 150 is classified as a built-up area. On our display monitor unit, these four categories appear as red, brown, green, and blue, respectively.

Another way of classifying the segmented image is to measure the texture of the original image with the segmented image as the guide for positioning the measuring window in the homogeneous regions. A Bayes classifier, or other suitable techniques, can be used to classify the sampled image windows.[6,7,8] The classified results can be written on the segmented image, as well as on the original image. This classification method turns out to be very useful for checking the misgrown regions that occur because of improper region growing.

Selection of an Optimum Threshold Value. The selection of a threshold value for the pixel-based region growing plays a crucial role in the entire process. The selection of the threshold value should be adaptively determined by the image data under analysis. Using an improperly predetermined fixed threshold value for region growing would lead to a serious mistake, and would end up in either undergrowing or overgrowing of the image. For our experimentation, the original SAR image of 512 by 512 pixels was first edge-enhanced, and smoothed with a low-pass filter. These two steps took the place of the first step discussed in appendix D. The smoothed image was then divided into 64 blocks of subimages with each block consisting of 64 by 64 pixels. The threshold determination method discussed by Nagao and Matsuyama[9] was applied to each block, and the minimum threshold value found for the subimages was selected as the threshold value for performing region growing for the entire image. The threshold determination method of Nagao and Matsuyama is provided in appendix D. The optimum threshold value was found to be 12 for the set of SAR images taken over the Elizabeth City, North Carolina, area. With this threshold value, the majority of images tested were region grown properly to yield four categories of area terrain features as desired.

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[6] N. D. Fox and P. F. Chen, Improving Classification Accuracy of Radar Image Using a Multiple-Stage Classifier, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, ETL-0502, September 1988, AD-A200 291.

[7] R. A. Hevenor and P. F. Chen, Pattern Classification Techniques Applied to High Resolution, Synthetic Aperture Radar Imagery, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, ETL-0443, November 1986, AD-A183 537.

[8] P. F. Chen, Preliminary Radar Feature Extraction and Recognition Using Texture Measurement, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, ETL-0315, February 1983, AD-A128 394.

[9] M. Nagao and T. Matsuyama, A Structual Analysis of Complex Aerial Photographs, Plenum Press, New York, 1980.

RESULTS

The automated segmentation and feature extraction software was successfully tested with several SAR images from the Elizabeth City, North Carolina, area. For illustration purposes, only the results obtained from two images will be presented. Figure 2 shows the first SAR test image, entitled UNF014. This image contains water, fields, forests, a township, and a road running from the top to the bottom of the image. Figure 3 illustrates the same image in pseudocolor, and as expected, the image is now easier to view and examine. For example, the regions that are smooth and have low gray values, such as water and roads, are now shown as yellow and easily identified. However, the edges, or boundaries, between fields and forests are not apparent. In order to enhance edges between regions, a Sobel edge operator was moved sequentially through the entire image (see figure 4). As a result, the enhanced boundaries divide the whole image into a number of large and small regions. However, none of the regions are smooth enough to be represented or displayed by a single pseudocolor. In addition, the Sobel operation produced unwanted noise that appeared as black spots on the image. In order to eliminate the spots and the noise appearing on the original image, a 3- by 3-pixel low-pass filter was passed through the whole image. The result of the low-pass filtering is illustrated in figure 5. Although the majority of spot-like noises were eliminated by applying the low-pass filter, none of the regions were smooth enough to be represented by a single gray value.

After low-pass filtering, a *region growing* technique was used to grow, or merge together, pixels of similar gray values in each region, so that the gray level of all pixels of each region would have the same value, and thus could be displayed by a single pseudocolor. A two-pass region growing technique was used that was developed at ETL.* With this two-pass region growing technique, all the images tested were properly grown or merged. A threshold value of 12 was used for the set of SAR imagery tested. The following observations can be made from the result:

1. The majority of pixels were properly grown or merged.

2. Four large regions with gray values of 4, 25, 65, and 150, respectively, corresponding to water, fields, forests, and boundary edges were created.

3. Ten more small regions, besides the large four regions stated above, were also produced. The gray values of these small regions ranged between 4 and 255.

The next step was to apply a simple pixel grouping routine to further group each pixel in small regions into one of the four large regions having a nearest gray value. Results of the pixel grouping on the SAR image, UNF014, are shown in figure 6. After the pixel grouping process, the entire image was segmented into exactly four categories. These categories had gray values of 4, 25, 65, and 150, respectively. On the display monitor they appeared as red, brown, green, and blue, respectively.

For classification or feature extraction, the regions having the gray values of 4, 25, and 65 were assigned as water, fields, and forests, respectively. The region that consisted of many boundary edges of gray value 150 was classified as the built-up area. The entire process of the automated segmentation and feature extraction is now complete. In order to assure the correctness of the feature extraction results, an alternate classification method based on the texture measurement and the Bayes classifier was used to classify the original image, UNF014, with the segmented image (see figure 6) acting as the guide for positioning the measuring window in the homogeneous regions. The classified results, using this method, were written over as characters on the segmented image as shown in figure 7. The same results can also be written over on the original image as well. Figure 8 shows the second SAR test image, entitled UNF026, in the original black and white form. The entire procedure described above was applied to this image. The results of the automated segmentation and feature extraction process are shown in figure 9.

*U.S. Army Engineer Topographic Laboratories

Figure 2. The First Original SAR Image, Entitled UNF014. in Black and White.

Figure 3. The Original SAR Image, UNF014, in Pseudocolor.

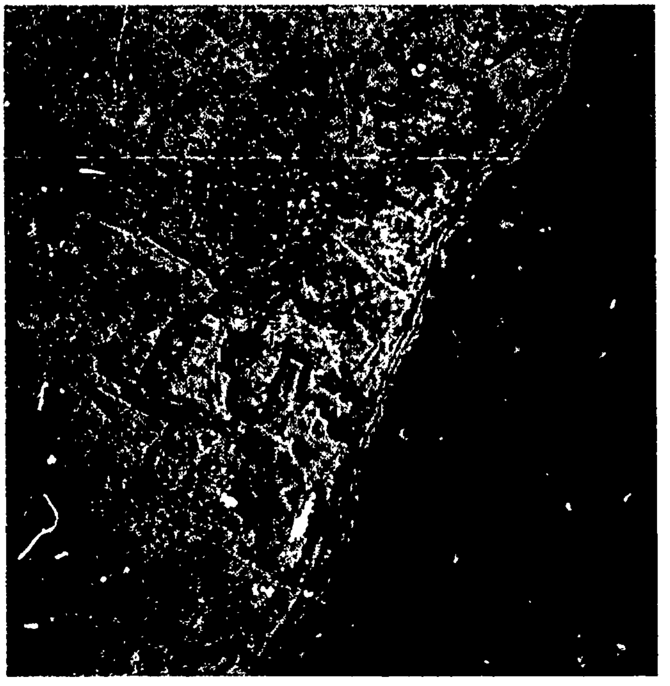

Figure 4. Edge-Enhanced SAR Image, UNF014.

Figure 5. The Result of Applying Low-Pass Filtering to the Image Shown in Figure 4.

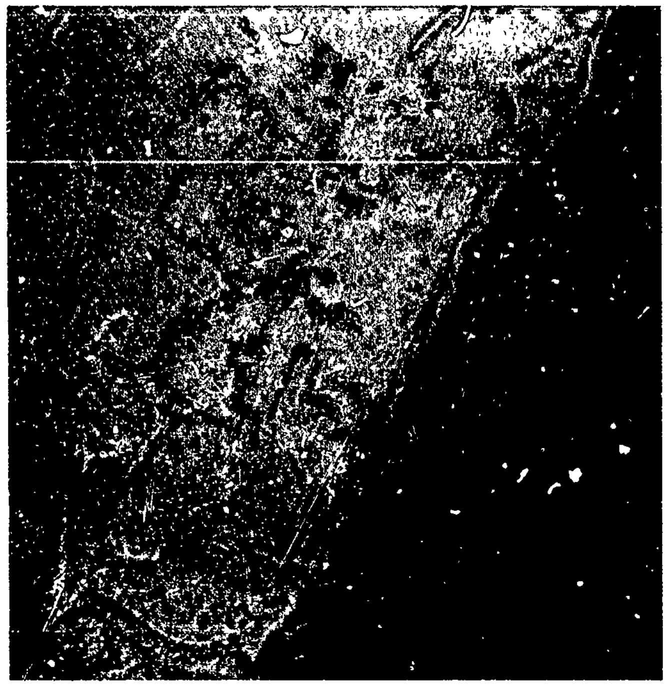

Figure 6. The Result of Applying Region Growing and Simple Pixel Grouping to the Image Shown in Figure 5.

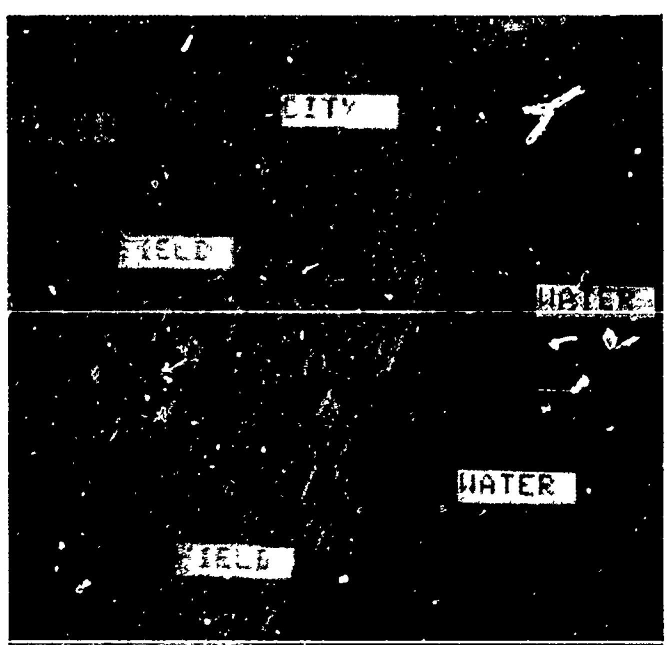

Figure 7. The Result of Applying Texture Measurement and Bayes Classifier to the Original Image, UNF014, is Superimposed on Figure 6.

Figure 8. The Second Original Image, Entitled UNF026, in Black and White.

Figure 9. The Final Result of Applying the Entire Sequence of Operations to the SAR Image, UNF026.

DISCUSSION

For some images, small blobs would appear over the large regions after applying the automated segmentation routines. An algorithm, called majority-merge-rules and based on the majority voting of four neighborhood pixels, was employed to eliminate the unwanted blobs. Consider a block of four neighboring pixels, P(i,j), P(i,j+1), P(i+1,j), and P(i+1,j+1), having the following corresponding gray values, G(i,j), G(i,j+1), G(i+1,j), and G(i+1,j+1), respectively. The majority voting rules are stated as follows:

1. If $G(i,j) = G(i,j+1) = G(i+1,j) = G(i+1,j+1)$, then no change occurs.

2. If any three G's are the same, then set the other G's equal to the others.

3. If any two G's have the same value and the other two are different, then set the last two G values equal to the first two G's.

4. If any two G's have the same value and the remaining two G's are equal, then do nothing.

5. If $G(i,j) \neq G(i+1,j) \neq G(i,j+1) \neq G(i+1,j+1)$, then do nothing.

Starting from the upper left pixel of the image, a block of four pixels will be sequentially examined following the majority voting rules discussed above. The sequence of examination will continue until the lower right corner pixel has been examined. Repeated application of the majority-merge-rules may be needed for eliminating relatively large blobs. One side effect of this algorithm is the thickening of boundary edges, which becomes worse as the algorithm is iteratively applied. A proper compromise is required here to keep the resultant segmented image in satisfactory condition.

FUTURE APPLICATIONS OF ALGORITHMS DEVELOPED

The automated segmentation algorithms presented above are very powerful basic tools, and can be used for automated extraction of various terrain features in the future. Presently, concepts for two automated feature finders, namely a water finder and a bridge finder, using the automated segmentation technique described above, have been successfully formulated. Additional algorithms will be required for both finders. The additional algorithms for the water finder are being developed. For the water finder, the following sequence of algorithms is suggested:

Sobel Edge Operation → Low-Pass Filtering → Two-Pass Region Growing → Simple Pixel Grouping → Simple Thresholding → Small Blob Elimination → Invert Image → Small Blob Elimination → Change Color.

The bridge finder envisioned will use the following sequence of algorithms:

Sobel Edge Operation → Low-Pass Filtering → Two-Pass Region Growing → Simple Pixel Grouping → Simple Thresholding → Connected Components → Straightness Measurement → Elongation Measurement → Neighborhood Inspection → Bridge Recognition.

As mentioned, the first four algorithms of both finders are adopted from the automated segmentation and feature extraction technique presented in this paper.

CONCLUSIONS

1. Automated segmentation of SAR imagery can be effectively accomplished by properly applying a set of image processing and computer vision algorithms sequentially, one at a time as discussed.

2. The two-pass region growing algorithm developed in-house is a very useful technique that produced almost the same gray value for each terrain category for all of the SAR images tested. Water, fields, forests, and boundaries always appeared as red, brown, green, and blue, respectively.

3. Feature extraction or classification can be done on the segmented image by identifying the different gray values of each region.

4. An alternate classification method based on texture measurement and the Bayes classifier can be applied to the original image, with the segmented image as the guide to position the measurement window. This method can be used as a good check for the first classification method. Both classification methods can be applied to an image, one at a time, if so desired. However, normally only one method will be required to classify images satisfactorily.

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Hevenor, R. A. and P. F. Chen, *Pattern Classification Techniques Applied to High Resolution, Synthetic Aperture Radar Imagery,* U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, ETL-0443, November 1986, AD-A183 537.

Nagao, M. and T Matsuyama, *A Structual Analysis of Complex Aerial Photographs,* New York: Plenum Press, 1980.

APPENDIX A. SOBEL EDGE OPERATOR

The Sobel operator is a 3- by 3-pixel nonlinear edge enhancement mask, which is multiplied sequentially with all pixel values in an image to produce a pattern of more pronounced edges.

The weights for the Sobel mask are shown below:

$$
\begin{array}{ccc}
-1 & 0 & 1 \\
-2 & 0 & 2 \\
-1 & 0 & 1
\end{array}
\qquad\qquad\qquad
\begin{array}{ccc}
1 & 2 & 1 \\
0 & 0 & 0 \\
-1 & -2 & -1
\end{array}
$$

x-direction   y-direction

Assume a block of 3 by 3 pixels to be multiplied with the Sobel mask centered at the point (i,j) and having a gray value distribution as given below:

$$
\begin{array}{ccc}
A_0 & A_1 & A_2 \\
A_7 & F(i,j) & A_3 \\
A_6 & A_5 & A_4
\end{array}
$$

Then, the resultant pixel value G(i,j), which will replace F(i,j), will be

$$| G(i,j) | = \sqrt{X^2 + Y^2},$$

where $X = (A_2 + 2A_3 + A_4) - (A_0 + 2A_7 + A_6)$,

and $Y = (A_0 + 2A_1 + A_2) - (A_6 + 2A_5 + A_4)$.

APPENDIX B. LOW-PASS FILTERS

The most commonly used low-pass filter consists of a mask of 3 by 3 pixels. It is multiplied sequentially with all pixel values on a given image to produce a smoothed pattern.

The weights for the low-pass mask are shown below:

$$\begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix}$$

Assume a block of 3 by 3 pixels to be multiplied with the low-pass mask centered at the point (i, j) and having a gray value distribution as given below:

$$\begin{matrix} A_0 & A_1 & A_2 \\ A_7 & F(i,j) & A_3 \\ A_6 & A_5 & A_4 \end{matrix}$$

Then, the magnitude of the resultant pixel G(i,j), which will replace F(i,j), will be

$$G(i,j) = \frac{1}{9}[\,A_0 + A_1 + A_2 + A_3 + A_4 + A_5 + A_6 + A_7 + F(i,j)].$$

For more sophisticated low-pass filters, the size of the mask can be increased to 5 by 5, or 7 by 7 pixels, and have values consisting of all 1's. However, the processing time of using these filters will be increased accordingly.

APPENDIX C. SIMPLE REGION GROWING

The simple region growing method, based on pixel gray value, consists of the following steps:

Step 1: If all pixels in a given image are labeled, then end; or take an unlabeled pixel and assign a new unused region number.

Step 2: If the absolute differences of gray value between the new labeled pixel and its neighboring pixels are less than the threshold value, respectively, then merge the neighboring pixels and assign them the same region number.

Step 3: Iterate Step 2 until no pixels adjacent to the newly labeled region can be merged.

Step 4: Go to Step 1.

APPENDIX D. THRESHOLD DETERMINATION METHOD

The following is the adaptive threshold determination algorithm used for our experimentation:

Step 1: Differentiate the smoothed image using the operator

$$d(i,j) = \max_{\substack{-1\le k\le 1\\ -1\le m\le 1}} | G(i,j) - G(i+k,j+m) | ,$$

where G(i,j) and d(i,j) denote the gray value and the differential value at a point (i,j), respectively.

Step 2: Divide the differentiated image into M blocks of 64- by 64-pixel subimages and make a histogram $h_n(d)$ of the differential values d(i,j) in the n^{th} block of subimage ($n = 1, 2, \cdots, M$).

Step 3: Use the Valley-Detection Algorithm. For each histogram $h_n(d)$, find the minimum value d_n which satisfies the following inequalities:

$$h_n(d_n) < h_n(d_n + k) \text{ for all } k = 1, 2, \cdots, N ,$$

$$d_n > d_n^* ,$$

where d_n^* denotes the differential value for which histogram $h_n(d)$ has the maximum population. The value of N is set initially to 9, but will be reduced from 9 to 8, and from 8 to 7, sequentially until a satisfactory result is obtained.

Step 4: Find the minimum value among the d_n for all blocks of subimages. and make it the threshold value T for all areas of the image; that is

$$T = \min_{1\le n\le M} d_n .$$